Work Project, presented as part of the requirements for the Award of a Master's degree in Economics from the Nova School of Business and Economics.

DO FIRMS CREATE IMMUNITY TO PRODUCTION NETWORK SHOCKS? EVIDENCE FROM THE COVID-19 GLOBAL PANDEMIC

Bernardo Miguel De Matos Mendes

29007

Work project carried out under the supervision of:

Professor Miguel A. Ferreira

January 2021

DO FIRMS CREATE IMMUNITY TO PRODUCTION NETWORK SHOCKS? EVIDENCE FROM THE COVID-19 GLOBAL PANDEMIC †

Bernardo Mendes

Nova School of Business and Economics

January 2021

Abstract

This paper studies whether firms learn from major supply-chain disruptions and adjust their production network to create immunity to future similar shocks. I use a ten-year time period comprehending two events that caused major production network disruptions - The Great East Japan Earthquake, in March 2011, and the COVID-19 global pandemic, in 2020. I first show that companies with Japanese suppliers during the Japanese earthquake diversified their production network in the years following the disaster. I then document that this learning mechanism provided immunity to the downstream propagation of the COVID-19 shock.

Keywords: COVID-19, Production Networks, Propagation Effect, Supply-Chain Diversification

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

† I would like to express my gratitude to my supervisor, Miguel A. Ferreira, for the invaluable guidance throughout this project. I also want to thank Manuel Adelino, Cláudia Custódio and Diogo Mendes, for the advice, support and encouragement. Finally, my thanks to Wenzhi Ding, Ross Levine, Chen Lin and Wensi Xie, for the availability to provide additional details on their study Ding et al. (2020), which served as the basis for a part of this paper.

1 Introduction

The global integration of modern economies, despite all the benefits conveyed by the vast number of people, capitals and trade flows across countries, constantly exposes companies to the risk of being negatively affected by shocks impacting their business partners (Menzly and Ozbas (2010), Boone and Ivanov (2012), Kelly et al. (2013)). As stated in Carvalho (2014), "A modern economy is an intricately linked web of specialized production units, each relying on the flow of inputs from their suppliers to produce their own output, which in turn is routed towards other downstream units". The global integration of firms' supply-chains and consequent high dependence on inputs produced in other parts of the globe is an important driver of the cross-country propagation of the negative consequences of such idiosyncratic shocks. In particular, one of the well-documented propagation mechanisms is the firm-level downstream propagation of shocks along the supply-chain, i.e., negative shocks disrupting firms' production networks are transmitted to the firm, impacting negatively its performance (Barrot and Sauvagnat (2016), Carvalho et al. (2016), Boehm et al. (2019), Pankratz and Schiller (2019)). Given the empirically documented firms' vulnerability to supply-chain disruptions, studying how firms can optimally react to this type of shocks and possibly hedge against future similar incidents is of major importance.

In this paper, I study whether firms learn from being exposed to major incidents in their supply-chain networks and adjust their production network in order to mitigate the negative effect of future identical events. In order to answer this question, I use The Great East Japan Earthquake, in March 2011, as a natural experiment to identify companies that suffered a severe disruption in their production network. Using a difference-in-differences approach, I show that companies with Japanese suppliers at the time of the earthquake (treatment group) diversified more their supply-chain network after this shock, when compared to companies without trade-relationships with Japanese firms in that period (control group). This adjustment mechanism occurred in two dimensions: on average, these companies increased not only the total number of suppliers but also the geographical dispersion of their production network, by expanding their trade-relationships to new countries. As of 2014, a firm belonging to the treatment group had, on average, 8.6 suppliers and 1.8 supplier countries more than a similar firm in the control group.

In order to understand if this adjustment mechanism is an optimal response to supply-chain shocks, I observe the market reaction to the downstream propagation effect of a posterior supply-chain disruption event. In specific, I use the COVID-19 global pandemic as a laboratory to study this hypothesis. I start by showing that COVID-19 brought severe consequences for companies at a worldwide scale, both directly and through the downstream propagation of the shock. This part of the paper is grounded on the recent work of Ding et al. (2020).[1] I extract country-level data on the number of COVID-19 reported infections for the first quarter of 2020, and build the variable *COVID-19*, defined as the weekly growth rate of cumulative COVID-19 cases in each country. I also compute firms' weekly stock market returns for the same time-period using dividend-adjusted closing stock prices. Moreover, in order to study the propagation of the shock via supplier-customer linkages, I obtain data on pre-pandemic business relationships among firms from FactSet Revere. Finally, several firm and economy characteristics are also considered. I document that an economy's exposure to the COVID-19 (measured by the variable *COVID-19*) impacts negatively and strongly the stock market performance of firms operating in that economy. I add to this paper by also examining the impact of the pandemic on several corporate fundamentals. I find that *Net Sales* decreased, on average, by more than 1% in each of the first two quarters of 2020, while *ROA* and *CAPEX/Assets* fell, on average, 0.85 and 0.32 percentage points per quarter in the first half of the year, respectively. Firms' indebtedness level increased during the pandemic period.

With respect to the propagation effect, this paper provides evidence supporting this phenomenon. I construct the variable *Suppliers' Exposure*, as the weighted average of *COVID-19* among the supplier countries, where the weights are given by the pre-pandemic number of suppliers from each country. Using the *Suppliers' Exposure* as a proxy for the severity of the supply-chain disruption, I isolate the impact of this variable on firms' weekly stock returns. Either considering only the market reaction in the first quarter of 2020 (as in Ding et al. (2020)) or extending the sample-period

[1] In this study, the authors start by evaluating the adverse effects of a firm's direct exposure to the COVID-19 virus on firms' stock market returns and, afterwards, test if several characteristics can affect firms' reaction to this unexpected event. In particular, they focus on firms' production networks to test the downstream propagation of the shock along the supply-chain.

until the end of August, the result is consistent: a higher exposure to the COVID-19 crisis in the network of suppliers (higher value of *Suppliers' Exposure*) impacts negatively firm's stock price. A one standard deviation increase in this variable is associated with a 0.22 and 0.13 percentage points drop in firms' weekly stock returns, respectively, for the two time-periods in analysis.

I then show that the impact of the downstream propagation of the COVID-19 crisis is less severe for firms previously affected by The Great East Japan Earthquake. This evidence strongly suggests that the production network's adjustment process undertaken by these firms in the years following the earthquake generated immunity to future similar supply-chain shocks.

This paper contributes to several strands of literature. Firstly, the results of this paper contribute to a vast body of research that looks at firms' vulnerability to supply-chain shocks. Previous empirical evidence uncovers the existence of downstream propagation of shocks affecting firms' suppliers. Barrot and Sauvagnat (2016) use data on natural disasters in the US since 1978 (this includes blizzards, earthquakes, floods, and hurricanes) combined with information on headquarters' locations and corporate performance indicators to show that 1) natural disasters have a considerable short-run impact on the annual sales growth of firms situated in affected areas; 2) firms with at least one affected supplier experience an average 2-3 percentage points decrease in annual sales growth and the impact is more pronounced in the case of hard-to-substitute inputs; 3) there is horizontal propagation of the negative impact for the companies' other non-affected suppliers. Using hurricanes data, Seetharam (2018) studies the spatial propagation of the impact of the disasters by examining linkages between disrupted and non-disrupted regions through plant ties within firms. Boehm et al. (2019) rely on the supply-chain disruption caused by the Great East Japan Earthquake from 2011 in order to evaluate cross-country propagation of shocks. Their work focus on the US affiliates of Japanese multinational companies and their main finding suggests that in the aftermath of the shock, the output produced by these firms dropped sizably, along with a decline in imports. Besides documenting the up and downstream propagation of the disruption caused by the earthquake, Carvalho et al. (2016) also estimate the overall macroeconomic impact of the catastrophe considering the propagation effects. Alternatively, Todo et al. (2014) also use this natural experiment to exploit firms' resilience to supply-chain disruptions. They document that firms with broader and more diversified production networks are more exposed to this idiosyncratic risk, delaying the recovery after the shock. Nonetheless, this negative effect is offset by the benefit conveyed by a diversified network of suppliers and customers, which allows for an accelerated replacement process of the harmed trade partners. Pankratz and Schiller (2019) draw similar conclusions regarding the role of the production networks in the propagation of shocks, in this case using extreme heatwaves and flooding incidents. Their study documents both direct and indirect large negative effects of these events in the revenues of the suppliers, as well as of their customers, through vertical propagation of the shock. This paper adds to this stream of literature by analyzing also the adaptation process that the customer firms decide to undertake in the aftermath of the shock. Accordingly, they find that these firms tend to diversify their production network towards lower climate risk suppliers.

This literature on the propagation effect innovates in relation to a vast stream of previous work focusing on how idiosyncratic microeconomic shocks are transmitted through industry linkages (Long and Plosser (1987), Horvath (1998), di Giovanni and Levchenko (2010), Acemoglu et al. (2012), Carvalho (2014)). The current availability of supplier-customer relationships data at the firm-level allows researchers to explore the propagation and amplification of idiosyncratic shocks at a more granular level, as it is performed in this study. Moreover, this study also documents new insights on the capacity that firms have to adjust their behavior after being negatively affected by shocks *(learning mechanism*) (Malerba (1992), Hayward (2002), Leary and Roberts (2005), Hu and Hassink (2017), Pankratz and Schiller (2019)).

Additionally, this study is also intimately related to the recent work of many researchers on studying the impact of the COVID-19 pandemic. In this regard, Baker et al. (2020) defend that government restrictions on commercial activity impacted much more strongly the US stock markets in the case of COVID-19 when compared to previous pandemics due to increasingly service-oriented nature of this economy. In a different perspective, using the timeline of the geographical propagation of the virus, Ramelli and Wagner (2020) show that the anticipation of the real effects brought by the health crisis were amplified through financial channels. Additionally, other researchers focused on how expectations changed during the pandemic (Giglio et al. (2020), Bartik et al. (2020)).

In summary, this paper brings new insights on the immunity that firms exposed to a supply-chain disruption in the past exhibit when facing a similar shock. Besides, the adjustment process that firms undertake after being negatively impacted by a supply-chain shock and that allows them to build such immunity is also one of the main contributions of this paper. Furthermore, this paper also explores new dynamics driven by production network shocks, by extending the time period of the analysis until the end of August 2020, comprehending the markets recovery period after the first global wave of COVID-19 cases. This extension provides the necessary framework to assess if firms with a higher exposure to COVID-19 in their production network experience a more difficult recovery when compared to similar less supplier-exposed firms. Finally, this paper adds to the literature by complementing the existing insights on the impact of the pandemic, both on stock market returns and on several corporate fundamentals (real effects).

The paper is organized as follows: the next section presents the data and methodology. Section 3 is focused on The Great East Japan Earthquake. In section 4, I document the production network diversification followed by affected firms in the aftermath of this event . In section 5, I quantify the adverse effects of the COVID-19 pandemic and document its downstream propagation effect. In section 6, I test the immunity to production network shocks. Finally, in section 7, I provide the concluding remarks of the paper. All relevant tables and figures can be found at the end of the paper.

2 Data and methodology

In this paper, I examine whether firms learn from major supply-chain disruptions and adjust their production network to create immunity to future similar shocks. In order to address this hypothesis, I focus on two events that occurred almost a decade apart. In the first place, I use The Great East Japan Earthquake, in March 2011, as an exogenous event that caused a major disruption in the production network of firms with suppliers affected by this disaster (Todo et al. (2014), Carvalho et al.

(2016), Boehm et al. (2019)). I study whether these companies adjusted their production network in the aftermath of the shock, in particular by diversifying their production network. In order to test if this adjustment mitigates the negative consequences of future similar shocks (*immunity effect*), I focus on the impact of the downstream propagation triggered by a posterior disruptive event. In this regard, I look at a major global crisis that caused severe disruptions in companies' supply-chain networks: the COVID-19 global pandemic.

I construct the sample in a forward-looking fashion as I need to observe how companies are affected in these two events (via supplier-customer relationships) and also the production networks adjustment process between them, if any. Moreover, for comparability purposes, I select a sample of firms following the recent literature on the negative effects of the COVID-19 crisis. In specific, I follow Ding et al. (2020).[2] Accordingly, the sample is composed by listed companies that are present in three distinct databases: 1) Thomson Reuters WORLDSCOPE, from which it is possible to retrieve corporate financial data; 2) Thomson Reuters ASSET4 ESG, that contains information on Corporate Social Responsibility (CSR) performance; 3) FactSet Revere, with data on supply-chain relationships.[3] Furthermore, stocks that were not actively traded in 2020 were excluded from the sample. As such, I end up with a sample of 3551 firms from 52 different countries.[4] Table A1 (in the appendix) displays the distribution of firms per country in the sample.

2.1 Production network diversification

In order to understand if affected firms (via downstream propagation of the shock) diversified their production network after The Great East Japan Earthquake (March 2011), I use a difference-in differences approach comparing the diversification level of two groups of firms: firms with Japanese

[2]This paper follows the first version of Ding et al. (2020) that can be found here: `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3586187`

[3]Ding et al. (2020) use the data available in the ASSET4 ESG database to show that firms with higher pre-pandemic CSR performance are less affected by the exposure to the COVID-19, suggesting that CSR activities induce stakeholders to take decisions that support the firm in response to a negative shock.

[4]The difference in the number of observations between this paper and Ding et al. (2020) is, most likely, the result of a different merging process with the supply-chain relationships dataset. The merging process followed by Ding et al. (2020) is not detailed in the paper. Hence, I was not able to reproduce the same steps in order to achieve the same final sample of firms.

suppliers in March 2011 (the treatment group) and firms without suppliers in this country at that time (the control group). I extract data on firms' trade relationships from FactSet Revere, for the years between 2008 and 2014. The decision to focus on this time-period relies on two main aspects: 1) by considering a relatively large time-period before the shock, it is possible to test the parallel trend assumption required for the correct identification under a difference-in-differences approach; 2) the post-earthquake period considered should not be too wide, as it increases the risk of confounding factors, but also not too short, as creating new supplier relationships may take years. To measure diversification, I use two different outcome variables: the *Total Number of Suppliers* and the *Number of Supplier Countries* at the end of each year, between 2008 and 2014. I am able to retrieve relationships' information for the complete period 2008-2014 for a subsample of 940 firms, from which 123 had suppliers in Japan in March 2011.

Furthermore, in this difference-in-differences setting, I also control for the *Share of Differentiated Inputs* of the firm in each year. Since Japanese industries are amongst the most advanced and innovative worldwide, producing technologically advanced products, a firm's necessity for differentiated inputs may be related to the existence of suppliers in Japan in March 2011 and, simultaneously, impacts the ability of firms to diversify its network of suppliers.[5] This variable is built according to the classification of goods traded in international markets based on Rauch (1999) and used by other authors (e.g., Giannetti et al. (2011) and Barrot and Sauvagnat (2016)). This list categorizes the inputs traded according to the sector (SIC 2-digit code) in which the good is produced. I then compute, for each year, the share of each firm's suppliers that belong to the industries classified as producing differentiated inputs.

2.2 The COVID-19 pandemic: direct impact and propagation effect

In the second part of this paper, I focus on the COVID-19 global pandemic and its implications. Following the approach in Ding et al. (2020), I analyze the impact of the COVID-19 global pandemic (both the direct impact and the propagation effect along the supply-chain) on stock market

[5]Source: https://www.eubusinessinjapan.eu/sectors

returns, while controlling for several firm and economic characteristics. Firstly, I focus on the same time period as the authors (between January and March 2020). I collect data on COVID-19 infections from the Coronavirus Resource Center managed by the Center for Systems Science and Engineering (CSSE) at the Johns Hopkins University (JHU).[6] This platform contains a comprehensive dynamic dashboard that compiles country-level daily information, starting on the 22nd of January 2020, on COVID-19 reported cases, tracing, testing and vaccination efforts, at a global level. I compute the weekly growth rate of cumulative confirmed infections to measure the propagation of COVID-19 in a given country:

$$\textit{COVID-19}_{c,t} = ln(1 + \text{Confirmed Infections}_{c,t}) - ln(1 + \text{Confirmed Infections}_{c,t-1}) \tag{1}$$

Where c and t denote, respectively, country and week.[7]

In what concerns firms' stock market returns, I extract firms' dividend-adjusted closing stock price data from Thomson Reuters Datastream. I then compute the percentage weekly stock return using the closing price at the last trading day of the week (Friday).[8]

In order to measure firms' suppliers' exposure to COVID-19, i.e., the different levels of exposure that firms face in their production network, the variable *Suppliers' Exposure* is built combining two sources of data. First, I obtain data on the companies' pre-pandemic supply-chain relationships (as of December 2019) from FactSet Revere.[9] This database aggregates information from corporate reports, annual fillings, press releases and investor presentations to build a global map of the business relationships among companies. One of the key features of this database is that it covers both direct and reverse disclosed relationships, i.e, connections disclosed by the reporting company (*direct disclosure*) and connections disclosed by firms doing business with the reporting company (*reverse disclosure*). As a result of this data collection approach, FactSet Revere comprises a vast

[6] See https://coronavirus.jhu.edu/map.html

[7] This variable is built using the cumulative number of confirmed cases at the last working day of the week, encompassing the variation of confirmed cases from Saturday to Friday in week t, in country c.

[8] I compute the weekly stock returns using the last trading day of each week to match the weekly growth rate of cumulative COVID-19 cases.

[9] Available in the Wharton Research Data Services (WRDS) platform.

number of interconnections between firms (more than 250.000 reported relationships in 2019), providing a broad and reliable data source of supply-chain relationships. In addition, this database also contains information regarding the industry (Standard Industrial Classification (SIC) codes) in which firms operate. I then combine data on pre-pandemic supply-chain relationships with the cumulative COVID-19 cases database to build a measure of each firm's suppliers' exposure to the COVID-19 crisis. I define it as follows:

$$\textit{Suppliers' Exposure}_{i,t} = \frac{\sum_{i=1}^{n} n_{i,c} \times \textit{COVID-19}_{c,t}}{n_i} \tag{2}$$

Where i, c and t are, respectively, firm, supplier country and week indexes. Besides, n_{i} is firm i's total number of suppliers and $n_{\mathrm{i,c}}$ refers to the number of suppliers of firm i located in country c. Analogously, *Suppliers' Exposure*$_{i,t}$ is the weighted average of *COVID-19* among the supplier countries, where the weights are given by the pre-pandemic number of suppliers from each country and *COVID-19* varies weekly. This variable is then merged with the main dataset using a combination of three company identifiers (FactSet ID, Company ID from Revere and International Securities Identification Number - ISIN).

Regarding the control variables, I obtain corporate financial data from the Thomson Reuters WORLDSCOPE database. In particular: *Firm size*, defined as the natural logarithm of the book value of total assets; *Leverage*, as the percentage of total debt over total assets; *Cash*, expressed as cash and equivalents divided by total assets; finally, *Return on Assets*, which corresponds to the ratio of net income over total assets. I use annual financial data from 2018, as in Ding et al. (2020).[10] As for country characteristics, I retrieve data from the World Development Indicators database (the World Bank's main cross-country source of development data) also for the year of 2018. The first set of variables relates to the economic performance of the country, comprising the natural logarithm of GDP *per capita*, and its evolution, captured by the growth rate of GDP. Besides, the percentage of the population aged above 65 years old is also added to the analysis

[10] The authors use data of 2018 as it was the most recent year of available data.

since a COVID-19 infection poses higher risk to the older generation. It is important to control for the share of population in this age range, since it may influence the promptness and severity of the governments' decisions to contain the spread of the virus. Lastly, as in Ding et al. (2020), a set of dummy variables for the legal origin of the economies is also included: English, French, German or Scandinavian origin. Legal origin's data is compiled in La Porta et al. (2008).

As previously mentioned, adding to the paper of Ding et al. (2020), I also explore the impact of COVID-19 on several firm's financial and performance indicators (real effects). To accomplish this, I extract firm's quarterly data from the Thomson Reuters WORLDSCOPE database, for the time-period comprehended between the first quarter of 2019 and the second quarter of 2020. It is important to mention that I am only able to explore this hypothesis for a subsample of firms, since the number of firms with disclosed financial information for the first two quarters of 2020 is fairly low when compared to the full sample. As outcome variables, I use *Log (Net Sales)*, *Debt/Assets*, *Return on Assets* and *CAPEX/Assets*. The set of firm-level controls included in the analysis comprises *Log(Total Assets)*, *Cash/Assets*, *Market-to-Book Ratio* and *Working Capital/Assets*.

2.3 Immunity to production network shocks

In the final part of this paper, I study if the supply-chain diversification undertaken by firms previously affected by the downstream propagation of the shock triggered by the Japanese earthquake created immunity to the downstream effect of the COVID-19 disruption. I retrieve data on firms' relationships for the year of 2011 from FactSet Revere. I make use of two different variables: *Dummy Japanese Suppliers 2011*, that takes the value of 1 if a firm had Japanese suppliers in March 2011 and 0 otherwise (extensive margin); and *Number of Japanese Suppliers 2011* which represents the number of Japanese suppliers of a firm in March 2011 (intensive margin). I end up with a subsample of 1987 firms, from which 171 had suppliers in Japan in March 2011.

Table 1 shows descriptive statistics for all the variables.[11] Panel B also reports summary statis-

[11] In the appendix: table A2 provides a detailed description of all the mentioned variables.

tics for Weekly Stock Return, *COVID-19* and *Suppliers' Exposure* for the extended time-period (January-August 2020). The average number of suppliers and supplier countries in the 2008-2014 period is 14,94 and 4.01, respectively. Moreover, in the first quarter of 2020, the sample average weekly stock market return was -2.37%, while the median was around -1%. This decline is also observed in figure A1 of the appendix, particularly in the period between the end of February and mid-March. Afterwards, the stock returns initiate an upward trend. This behavior is in line with the overall behavior registered in several stock indexes (see appendix, figure A2). On average, COVID-19 infections increase by almost 60% each week in the first quarter of 2020, in the countries represented in the sample (the average of *COVID-19* is 0.59). Finally, *Suppliers' Exposure* has an average of 0.72 and a standard deviation of 0.79, indicating large disparities in firm's exposure to COVID-19 through their supply-chain network.

3 The Great East Japan Earthquake

On March 11, 2011, a 9.0 magnitude earthquake hit the Pacific Ocean, with its epicenter only 77km off the east cost of the Japanese region of Tōhoku. This catastrophe, entitled by the Japanese Government as The Great East Japan Earthquake, was the most devastating earthquake ever registered in Japan and it is placed fourth in the list of most powerful earthquakes since 1900 (Boehm et al., 2019).[12] Besides, the main tremor generated a massive tsunami that reached the eastern coast of Honshu (the largest Japanese island) a few minutes after the quake, flooding more than 500 square kilometers of land, inundating entire towns and villages (Ishiwatari, 2014). The impact of the tsunami brought tremendous losses and destruction to several Japanese coastal areas. The geographical distribution of the impact of the earthquake can be found in figure A3 of the appendix. Moreover, this catastrophe also triggered a nuclear crisis. The 11 nuclear power plants in the north-east Japan stopped working as several damages were reported. The most well-known case is the accident in the Fukushima nuclear reactor, that rapidly became a level 7 nuclear event (the highest

[12]The first three positions of this ranking are occupied, respectively, by the Valdivia Earthquake (Chile, 1960), the 1964 Great Alaska Earthquake and the Sumatra-Andaman Islands Earthquake, in 2004. *Source*: US Geological Survey.

level in the International Nuclear and Radiological Event Scale (INES)), as the radiation near the reactor started increasing (Norio et al., 2012). These nuclear accidents led to considerable power outages that were persistent for months and undermined the recovery of the economic activity in the affected areas (Boehm et al., 2019). Overall, the Japan's Cabinet Office estimated the impact of the earthquake and its aftermaths with a direct economic cost of 16.9 trillion yens, or equivalently, 210 billion US dollars (Ishiwatari, 2014). Carvalho et al. (2016) estimated that the disaster resulted in a 0.47 percentage points decline in Japan's real GDP in the year following the earthquake. Additionally, in figure A4, we can see the drop in Japan's industrial production caused by the The Great East Japan Earthquake. Between February and March 2011, the industrial production decreased by more than 15 percentage points and only returned to pre-earthquake levels a few months later. Naturally, the sizable drop in industrial output also caused a decrease in Japan's exports. Focusing on the US imports from Japan, figure A5 shows a sharp decrease in imports in the period immediately after the earthquake.[13] Even more interesting is the impact on the US production: in the aftermath of the earthquake, the deviation from the trend for the US manufacturing and durable goods' production is clearly negative, as depicted in figure A6. Hence, it is possible to conclude that this shock brought not only severe consequences to the Japanese economy, but also to its trading partners, illustrating the propagation of the shock (Todo et al. (2014), Carvalho et al. (2016), Boehm et al. (2019)).

4 Production network diversification

In order to examine the adjustment process adopted by the firms in response to the supply-chain disruption brought by The Great East Japan Earthquake, I explore the production network's diversification as the possible adjustment mechanism. As suggested by Pankratz and Schiller (2019), when facing a disruption in their supply-chain, firms react by diversifying their supplier network and replacing high-risk by lower-risk suppliers in terms of exposure to extreme climate circum-

[13] I decided to use the US imports from Japan in this illustrative example because most of the in-sample firms are located in this country.

stances. The benefits of suppliers' diversification are also documented in Todo et al. (2014), since firms can more easily substitute affected suppliers.

In particular, I test if firms with Japanese suppliers in March 2011 diversify their supply sources after being negatively impacted by the earthquake due to the propagation of the shock. Note that in this framework I use the existence of relationships with Japanese suppliers in March 2011 as a proxy for a past supply-chain disruption. The lack of data about the exact location of firms' suppliers in 2011 by prefecture prevents me from identifying precisely which firms had suppliers in the most affected areas of Japan and, consequently, were indirectly affected by the earthquake via downstream propagation of the shock. However, as it was previously shown, this earthquake brought severe consequences for the Japanese economy as a whole, with a significant decrease in the Japanese industrial production. This suggests that the consequences of the earthquake generalized over the country, and even firms not directly affected by the earthquake suffered with this shock. One possible argument supporting this view is the interruption of many supply-chains within the country, impairing non-affected firms' production. Nonetheless, still in this regard, this shortcoming is very likely to bias the estimates against finding any result.

To examine this hypothesis, I use a difference-in-differences setting, comparing the diversification level of treatment and control groups over the 2008-2014 period. In figures A7a and A7b (in the appendix), the evolution of the simple average outcome values for both groups of firms suggests a higher degree of diversification for the treatment group in the years following the earthquake. As a main specification, I regress each of the outcome variables on the *Dummy Japanese Suppliers 2011* (the treatment variable), a dummy for each year between 2008 and 2014, and the interaction between each year-dummy and the treatment variable. Furthermore, I also control for the *Share of Differentiated Inputs* of the firm in each year. Finally, I include also firm, economy-year and industry-year fixed effects, and standard errors are clustered at the economy-year level:

$$y_{i,t} = \alpha_0 + \theta \times Dummy\ Jap.\ Suppliers\ 2011_i + \sum_{t=2008}^{2014} \beta_t \times Dummy_t + \sum_{t=2008}^{2014} \gamma_t \times Dummy_t \times Dummy\ Jap.\ Suppliers\ 2011_i + \lambda \times Share\ of\ Diff.\ Inputs_{i,t} + \delta_i + \delta_{c,t} + \delta_{j,t} + \varepsilon_{i,t} \quad (3)$$

Where *i, t, c, j* are, respectively, firm, year, country and industry indexes.

Columns 1 and 2 of table 2 and figures A8a and A8b (in the appendix) report the results, with 2008 as the base year. For both outcome variables, the parallel trend assumption is verified, as the coefficients in the years before the shock are not statistically significant. As such, we disregard the existence of a pre-shock trending behavior in the difference of the outcomes between both groups. Moreover, the positive and statistically significant coefficients after the shock confirm the higher degree of diversification for the firms with Japanese suppliers during the earthquake. In fact, this group of firms increased more both the number of suppliers and supplier countries than the control group. Additionally, I find that the difference grows over time, which suggests that the diversification of supply sources might have been difficult (and costly) in the short term. In 2014, a firm belonging to the treatment group (firms with Japanese suppliers in March 2011) had, on average, 8.6 suppliers and 1.8 supplier countries more than a similar firm in the control group. As alternative specifications, I use the *Number of Japanese Suppliers 2011* as the treatment variable (columns 3 and 4); or use the *Post* variable, instead of year dummies (columns 5 and 6).[14] The results are robust in all specifications.

In summary, after being negatively affected by the earthquake via downstream propagation of the shock, firms increase not only the number of suppliers, but also the geographical dispersion of their network of suppliers. By doing so, they enjoy the benefits of a diversified network of suppliers, which are well-documented on the literature.

5 The COVID-19 global pandemic

The outbreak of the COVID-19 pandemic brought unprecedented consequences at a global scale, forcing many governments to trade-off economic activity for restrictive health policies in order to control the rise in infections. The disease, which was first identified in December 2019, in Wuhan, China, quickly spread out, affecting virtually all economies worldwide. The unexpected nature of this event and its implications for the business sector (which will be documented in this section)

[14] The *Post* variable takes the value of 1 for the years 2011-2014, and 0 otherwise.

provide the ideal setting to address the *immunity* hypothesis of this paper.

5.1 Adverse effects of the COVID-19 pandemic

In order to evaluate the direct adverse effects of the COVID-19 global pandemic on stock market returns, the following fixed-effects model is estimated:

$$Return_{i,t} = \alpha_0 + \beta_1 \times \textit{COVID-19}_{c,t} + \eta X'_{i,2018} \times \textit{COVID-19}_{c,t} + \gamma Z'_{c,2018} \times \textit{COVID-19}_{c,t} + \delta_i + \delta_{j,t} + \varepsilon_{i,t} \quad (4)$$

Where *i, t, c* and *j* are, respectively, firm, week, country and industry indexes. $X'_{i,2018}$ and $Z'_{i,2018}$ correspond to a set of firm and economy pre-pandemic traits, respectively. Besides firm fixed-effects (δ_i), I also include industry-week fixed-effects ($\delta_{j,t}$), controlling for any time-invariant differences across firms and time-varying attributes across industries.[15] Standard errors are clustered at the economy level. Initially, I exclude the interaction terms between *COVID-19* and both firm and economy traits. This allows me to quantify the economic magnitude of the *COVID-19*'s impact on firms' weekly stock returns.[16] Column 1 of table 3 presents the results. If COVID-19 infections grow at the sample average value in an economy, the stock returns of firms operating in that economy fall, on average, by around 0.44 percentage points more per week (0.59×0.744), which is equivalent to 18.5% of the average value of weekly stock returns in the first quarter of 2020 (-2.37%). In column 2, I present the results of the full specification. The negative and significant *COVID-19* coefficient confirms the negative impact of an economy's exposure to the pandemic on the stock market performance of firms operating in that economy.

I also explore the impact of COVID-19 on several firm's financial and performance indicators. I use a fixed effects specification regressing each of four variables – *Log (Net Sales)*, *Debt/Assets*, *Return on Assets* and *CAPEX/Assets* – on two dummy variables, one for each quarter of 2020, and

[15]Industry-week fixed effects are build using the SIC 2-digit industry code.

[16]With the inclusion of the interaction terms with *COVID-19*, the partial effect of this variable on the weekly stock returns depends on the specific firm and economy characteristics.

a set of firm-level controls:[17]

$$Y_{i,q} = \alpha_0 + \beta_1 \times 2020\text{ Q1} + \beta_2 \times 2020\text{ Q2} + \gamma X'_{i,q} + \delta_i + \varepsilon_{i,q} \tag{5}$$

Where i is the firm index, and q is the quarter index. In this model, the two dummy variables capture the behavior of the outcome variables during the COVID-19 global pandemic, while conditioning out time-invariant differences across firms (due to the inclusion of firm fixed effects (δ_i)), and also controlling for other relevant time-varying firms' attributes ($X'_{i,q}$). Standard errors are clustered at the economy level. Table 4 reports the results. Regarding firms' performance, *Net Sales* decreased, on average, by 1.1% and 1.6% in the first and second quarter of 2020, respectively; the *Return on Assets* was also negatively affected, decreasing on average by more than 0.85 percentage points per quarter in the first half of the year. Oppositely, the indebtedness level of the firms increased during this period (column 3).[18] In the last column of table 4, we observe that the ratio of capital expenditures to total assets also declined in the first half of 2020, at an average rate of approximately -0.32 percentage points per quarter. Finally, it is worthwhile to note that for all the analyzed outcome variables, the negative impact of the pandemic is intensified from the first to the second quarter of 2020, consistent with the long-lasting nature of the shock.

5.2 Downstream propagation of the shock along the supply-chain

The emergence of the COVID-19 pandemic, besides disturbing companies' business models and forecasts for the future, also caused enormous disruptions in companies' supply-chain networks.[19] Many countries in which firms have their suppliers located ceased temporarily their economic activity as a response to the increasing number of reported infections, forcing workers and firms to stop producing. Figure A9 depicts the sharp decrease in the world's merchandise trade volume

[17] The natural logarithm of *Net Sales* is used for interpretation purposes.

[18] This result can be interpreted as a mechanism adopted by the firms to smooth the negative impact generated by the almost complete interruption of the economic activity in many countries. In fact, many governments resorted to credit lines as one of the main instruments to help firms dealing with the economic consequences of the pandemic.

[19] See https://www.technologyreview.com/2020/11/13/1012073/pandemic-prepared-ai-for-alibaba-singles-day/

index in the first quarter of 2020. Taking this into consideration, this unexpected shock provides an ideal setting to examine the existence of the downstream propagation effect of supply-chain shocks. I focus exclusively on the stock market returns as the outcome variable, and isolate the impact of the propagation effect by comparing firms with different levels of exposure to the pandemic in their network of suppliers. Alternatively, previous literature on the topic documents this phenomenon using other indicators, such as firms' turnover and/or cost of goods sold. However, these studies made use of a wider time period, allowing authors to assess the propagation effect on these variables with some delay (Barrot and Sauvagnat (2016), Pankratz and Schiller (2019)). Since this is not possible due to the lack of quarterly corporate data, I devote my attention to the propagation effect on stock market returns, that are expected to respond immediately to shocks. Following Ding et al. (2020), I measure risk exposure through the supply-chain using the variable *Suppliers' Exposure* and quantify its impact on the firms' stock market returns for the 13 weeks between January and March 2020. I aim to assess whether the impact of *COVID-19* is more pronounced for firms with a higher *Suppliers' Exposure*, which suggests the propagation of the shock. Columns 3 and 4 of table 3 report the results. In column 4, I include economy-week fixed effects to control for all time-varying economy factors, which omits *COVID-19* and all the variables in *Economy Traits * COVID-19*. The result is robust in both specifications. Firms with a network of suppliers located in countries more exposed to the COVID-19 experience, on average, a stronger decline in their stock price as a consequence of the pandemic. This result confirms the downstream propagation of the shock. Regarding the magnitude of the coefficients, focusing on column 4, a one standard deviation increase in a firm's *Suppliers' Exposure* intensifies the negative stock price reaction by 0.22 percentage points (0.79×0.284). Furthermore, I explore the robustness of the propagation effect over time by extending the time period to include the 35 weeks comprised since the beginning of the year until the end of August 2020. Note that this sample-period includes the markets' recovery phase after the first wave of the COVID-19 pandemic, which started in the end of the first quarter of 2020 (the sample average weekly stock return in April-August is 1.49%). The results are reported in columns 5 and 6 of table 3. The coefficient in column 6 indicates that a one standard deviation increase in *Suppliers' Exposure* raises the negative stock prices' reaction, on average, by 0.13 percentage points (0.57×0.232). Although the impact is reduced in absolute terms, the propagation effect seems to be robust over time: a higher *Suppliers' Exposure* (which proxies for a more severe disruption in firm's supply-chain network) impacts negatively firms' stock prices in 2020, even when considering the upturn phase of the market.

6 Empirical evidence of immunity to production network shocks

The last section of this paper tests if the firms affected by The Great East Japan Earthquake via downstream propagation of the shock (and that diversified their production network), are able to create immunity to future similar shocks. In order to test this hypothesis, I examine if the impact of the supply-chain disruption caused by the COVID-19 global pandemic (given by the variable *Suppliers' Exposure*) is less severe for this group of firms. In particular, using the stock market returns as the outcome variable, I compare the *Suppliers' Exposure* effect for the control and treatment groups. By interacting the *Suppliers' Exposure* with each of the variables *Dummy Japanese Suppliers 2011* and *Number of Japanese Suppliers 2011* and assessing its sign and significance, it is possible to test the hypothesis that firms are able to create immunity to supply-chain shocks after having been exposed to an identical shock in the past. I apply the same specifications as in columns 3 and 4 of table 3 with these additional interaction terms. Columns 1-4 of table 5 reports the results for the first quarter of 2020. The positive and statistically significant coefficients on the interaction terms indicate that firms with Japanese suppliers in March 2011 are less affected via supply-chain propagation of the COVID-19 shock than firms with no suppliers in that country during the earthquake. This finding suggests that firms with a supply-chain disruption in the past are able to adjust their production network (through diversification) to create a certain degree of immunity to identical shocks. The coefficient in column 2 suggests that the adjustment may be so important that these firms fully avoid the consequences of this shock. Among these companies, a one standard deviation increase in *Suppliers' exposure* increases the weekly stock return by 0.1

percentage points $[(-0.167+0.295)\times 0.79]$. As a robustness check, I extend the sample period until the end of August 2020 (columns 5 and 6), and the result persists.

The exogenous nature of both shocks considered (the Great East Japan Earthquake and the COVID-19 global pandemic) provides strong reasons in favor of the reliability of these findings. Endogeneity would be a concern in the case of the omission of a variable that is simultaneously correlated with the firms' stock market returns in 2020 and the existence of Japanese suppliers in March 2011. However, some arguments can be pointed out against this scenario. First, the unexpected nature of the earthquake did not allow firms to adjust their production network immediately before the disaster, by substituting Japanese suppliers by others not affected by the catastrophe. This means that the existence of relationships with Japanese suppliers was driven by other factors, such as the firm´s industry, the geographical proximity to Japan, or the necessity of specific inputs produced in this country, for instance. Potentially, some of these factors may also be correlated with the firms' stock market reaction to COVID-19. However, in this regard, I saturate the model with fixed effects (firm, economy-week and industry-week fixed effects), as well as firm traits interacted with *COVID-19*, which have the purpose of controlling for all these aspects, minimizing the possibility of an endogenous relations between these two variables. Finally, a fundamental argument that must be emphasized is that firms with the past supply-chain disruption (which are aware of the negative impact through the propagation effect), did not have enough time to adjust their production network immediately before the COVID-19 pandemic, due to the unexpected nature of the event. Taking these arguments into account, the result suggests that the adjustment process is undertaken in anticipation of a new shock, so that firms benefit from this learning mechanism when facing a new unexpected suppliers' disruption event.

7 Conclusion

Firms' vulnerability to production network shocks has been documented in the literature. In particular, the firm-level downstream propagation of shocks has been confirmed using several different natural experiments (hurricanes, blizzards, climate change, earthquakes...). As the growing pace of supply-chains' global integration constantly exposes firms to shocks of this nature, it is of major importance to understand what may be the optimal reaction of firms after being negatively affected by these idiosyncratic shocks.

This paper uses a ten-year time range to study whether firms are able to create immunity to supply-chain shocks after having been exposed to a similar shock in the past. This time-period comprehends two major events: The Great East Japan Earthquake and the COVID-19 global pandemic. I start by showing that companies with Japanese suppliers during the Japanese earthquake diversified their production network in the years following the disaster. This evidence is suggestive of an adjustment mechanism that may help firms mitigating the negative impact of a future similar event. In order to show that this adjustment process is effective, I study how attenuated the negative stock market reaction is to the downstream propagation effect of the COVID-19 pandemic for these firms. In this regard, I start by analyzing the direct impact of this crisis on firms' stock market returns and on several firm fundamentals. I show that firms' stock prices decreased sharply in the first quarter of 2020 as a result of the propagation of the virus in the countries where firms are located. Besides, the negative impact on firms' fundamentals is exacerbated from the first to the second quarter of 2020, consistent with the persistent nature of this shock. I then document the downstream propagation of the COVID-19 shock, by showing that firms with a higher disruption in their production network experience a higher decline in their stock prices. After confirming the downstream propagation of the COVID-19 shock, I show that firms with a past disruption in their network of suppliers (proxied by firms with Japanese suppliers during The Great East Japan Earthquake) build immunity to identical shocks after diversifying their supply-chain network, specifically the COVID-19 pandemic, almost a decade later.

These findings provide important insights on how firms are able to adjust their network of suppliers to hedge against supply-chain disruptions. In the growing "intricately linked web of specialized production units" (Carvalho, 2014) in which economies operate, findings such as the ones described in this paper assume an increasingly prominent role.

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The Network Origins of Aggregate Fluctuations. *Econometrica*, 80(5):1977–2016.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K. J., Sammon, M. C., and Viratyosin, T. (2020). The unprecedented stock market impact of covid-19. Technical report, National Bureau of Economic Research.

Barrot, J.-N. and Sauvagnat, J. (2016). Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks *. *The Quarterly Journal of Economics*, 131(3):1543–1592.

Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., and Stanton, C. (2020). The impact of covid-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences*, 117(30):17656–17666.

Boehm, C. E., Flaaen, A., and Pandalai-Nayar, N. (2019). Input linkages and the transmission of shocks: firm-level evidence from the 2011 tōhoku earthquake. *Review of Economics and Statistics*, 101(1):60–75.

Boone, A. L. and Ivanov, V. I. (2012). Bankruptcy spillover effects on strategic alliance partners. *Journal of Financial Economics*, 103(3):551–569.

Carvalho, V. M. (2014). From micro to macro via production networks. *Journal of Economic Perspectives*, 28(4):23–48.

Carvalho, V. M., Nirei, M., Saito, Y., and Tahbaz-Salehi, A. (2016). Supply chain disruptions: Evidence from the great east japan earthquake. *Columbia Business School Research Paper*, (17-5).

di Giovanni, J. and Levchenko, A. A. (2010). Putting the parts together: Trade, vertical linkages, and business cycle comovement. *American Economic Journal: Macroeconomics*, 2(2):95–124.

Ding, W., Levine, R., Lin, C., and Xie, W. (2020). Corporate Immunity to the COVID-19 Pandemic. NBER Working Papers 27055, National Bureau of Economic Research, Inc.

Giannetti, M., Burkart, M., and Ellingsen, T. (2011). What you sell is what you lend? explaining trade credit contracts. *The Review of Financial Studies*, 24(4):1261–1298.

Giglio, S., Maggiori, M., Stroebel, J., and Utkus, S. (2020). Inside the mind of a stock market crash. Technical report, National Bureau of Economic Research.

Hayward, M. L. (2002). When do firms learn from their acquisition experience? evidence from 1990 to 1995. *Strategic management journal*, 23(1):21–39.

Horvath, M. (1998). Cyclicality and sectoral linkages: Aggregate fluctuations from independent sectoral shocks. *Review of Economic Dynamics*, 1(4):781–808.

Hu, X. and Hassink, R. (2017). Exploring adaptation and adaptability in uneven economic resilience: A tale of two chinese mining regions. *Cambridge Journal of Regions, Economy and Society*, 10(3):527–541.

Ishiwatari, M. (2014). *Learning from megadisasters: Lessons from the Great East Japan Earthquake*.

Kelly, B. T., Lustig, H. N., and Van Nieuwerburgh, S. (2013). Firm volatility in granular networks. *NBER Working paper*, (w19466).

La Porta, R., Lopez-de Silanes, F., and Shleifer, A. (2008). The economic consequences of legal origins. *Journal of economic literature*, 46(2):285–332.

Leary, M. T. and Roberts, M. R. (2005). Do firms rebalance their capital structures? *The journal of finance*, 60(6):2575–2619.

Long, J. B. and Plosser, C. I. (1987). Sectoral vs. aggregate shocks in the business cycle. *The American Economic Review*, 77(2):333–336.

Malerba, F. (1992). Learning by firms and incremental technical change. *The economic journal*, 102(413):845–859.

Menzly, L. and Ozbas, O. (2010). Market segmentation and cross-predictability of returns. *The Journal of Finance*, 65(4):1555–1580.

Norio, O., ye, T., Kajitani, Y., Shi, P., and Tatano, H. (2012). The 2011 eastern japan great earthquake disaster: Overview and comments. *International Journal of Disaster Risk Science*, 2.

Pankratz, N. and Schiller, C. (2019). Climate change and adaptation in global supply-chain networks. *Available at SSRN 3475416*.

Ramelli, S. and Wagner, A. F. (2020). Feverish stock price reactions to covid-19.

Rauch, J. E. (1999). Networks versus markets in international trade. *Journal of international Economics*, 48(1):7–35.

Seetharam, I. (2018). The indirect effects of hurricanes: Evidence from firm internal networks. Technical report, mimeo, Stanford University.

Todo, Y., Nakajima, K., and Matous, P. (2014). How do supply chain networks affect the resilience of firms to natural disasters? evidence from the great east japan earthquake. *Journal of Regional Science*, 55.

Table 1. Descriptive Statistics

	Mean	Std. Dev.	p10	p25	p50	p75	p90	No. Obs.
Panel A: Diversification 2008-2014								
Total Number of Suppliers	14.94	25.75	1.00	3.00	7.00	15.00	35.00	6580
Number of Supplier Countries	4.01	4.32	1.00	1.00	2.00	5.00	9.00	6580
Share of Differentiated Inputs (%)	0.31	0.32	0	0	0.21	0.5	0.83	6580
Panel B: Replication and extended time period								
Weekly Stock Return (First Quarter 2020) (%)	-2.37	8.97	-14.10	-6.23	-1.02	2.10	6.11	45499
Weekly Stock Return (January-August 2020) (%)	0.20	8.52	-9.39	-3.75	0.05	3.93	9.30	122708
COVID-19 (First Quarter 2020)	0.59	0.88	0.00	0.00	0.00	1.10	1.84	676
COVID-19 (January-August 2020)	0.32	0.60	0.00	0.01	0.06	0.33	1.10	1820
Suppliers' Exposure (First Quarter 2020)	0.72	0.79	0.00	0.00	0.43	1.23	1.90	45499
Suppliers' Exposure (January-August 2020)	0.36	0.57	0.00	0.05	0.10	0.38	1.16	122708
Firm size	14.99	1.66	12.88	13.90	14.97	16.07	17.13	45499
Leverage	27.97	22.47	0.30	12.18	26.19	39.57	53.64	45499
Cash	15.96	18.61	1.61	4.19	9.46	19.47	39.88	45499
Return on Assets	4.35	16.11	-3.35	2.55	5.48	9.32	14.97	45499
Logarithm of GDP per capita	9.95	1.07	8.27	9.19	10.17	10.78	11.05	52
GDP growth	2.99	1.82	1.29	1.86	2.65	3.96	5.35	52
% Pop. above 65	12.99	6.36	4.31	7.12	14.02	18.90	20.10	52
Panel C: Quarterly Fundamentals								
Log (Net Sales)	15.20	2.64	12.43	13.59	14.87	16.81	18.70	4143
Return on Assets	3.87	11.23	-7.90	0.74	4.69	9.18	15.15	4054
Debt/Assets	26.00	19.30	1.15	10.38	24.69	37.89	50.30	4095
CAPEX/Assets	4.90	5.45	0.45	1.38	3.13	6.22	11.16	3991
Log (Total Assets)	15.25	2.05	12.77	13.86	15.01	16.54	17.97	3455
Cash/Assets	0.11	0.12	0.01	0.03	0.08	0.15	0.25	3344
Working Capital/Assets	0.15	0.18	-0.06	0.03	0.13	0.25	0.39	3091
Market-to-Book Ratio	3.66	5.88	0.71	1.14	2.06	4.15	8.92	3317

Notes: In panel A, all variables are firm-year level. In panel B, *COVID-19* is built using country-week data; economy traits (Logarithm of GDP *per capita*, GDP growth and % pop. above 65) are built using country-level data; all the other variables are firm-week level. In Panel C, all variables are firm-quarter level.

Table 2. Production network's diversification 2008-2014

	(1) Number of Supplier Countries	(2) Total Number of Suppliers	(3) Number of Supplier Countries	(4) Total Number of Suppliers	(5) Number of Supplier Countries	(6) Total Number of Suppliers
Post * Dummy Jap. Suppliers 2011					1.094***	5.017***
					[0.208]	[1.389]
D. 2009 * Dummy Jap. Suppliers 2011	0.125	-0.135				
	[0.295]	[1.853]				
D. 2010 * Dummy Jap. Suppliers 2011	0.425	-0.145				
	[0.269]	[1.682]				
D. 2011 * Dummy Jap. Suppliers 2011	0.947***	1.095				
	[0.260]	[1.518]				
D. 2012 * Dummy Jap. Suppliers 2011	1.241***	3.972***				
	[0.247]	[1.450]				
D. 2013 * Dummy Jap. Suppliers 2011	1.173***	6.026***				
	[0.269]	[1.544]				
D. 2014 * Dummy Jap. Suppliers 2011	1.752***	8.602***				
	[0.366]	[2.546]				
D. 2009 * Number of Jap. Suppliers 2011			0.026	0.049		
			[0.022]	[0.083]		
D. 2010 * Number of Jap. Suppliers 2011			0.117***	0.540***		
			[0.021]	[0.074]		
D. 2011 * Number of Jap. Suppliers 2011			0.068***	-0.032		
			[0.021]	[0.156]		
D. 2012 * Number of Jap. Suppliers 2011			0.358***	3.793***		
			[0.021]	[0.084]		
D. 2013 * Number of Jap. Suppliers 2011			0.470***	5.181***		
			[0.021]	[0.110]		
D. 2014 * Number of Jap. Suppliers 2011			0.501***	5.980***		
			[0.029]	[0.108]		
Share of Diff. Inputs	0.438**	1.944***	0.448**	1.972***	0.445**	1.995***
	[0.194]	[0.632]	[0.194]	[0.585]	[0.194]	[0.640]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Economy-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	6510	6510	6510	6510	6510	6510
No. Firms	930	930	930	930	930	930
Adjusted R-Squared	0.787	0.855	0.789	0.871	0.786	0.854

Notes: This table reports the results of the difference-in-differences specifications to study the production network diversification after The Great East Japan Earthquake, in March 2011. The inclusion of firm, economy-year and industry-year fixed effects omits the treatment variable (*Dummy Japanese Suppliers 2011, Number of Japanese Suppliers 2011 and Post*) and all the year-dummies. Robust standard errors clustered at the economy -year level are reported in brackets. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Direct impact and propagation effect of COVID-19 on firms' stock returns

	First Quarter 2020				**January-August 2020**	
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19	-0.744***	-4.088***	-3.605**		-3.941**	
	[0.143]	[1.415]	[1.427]		[1.642]	
Suppliers' Exposure			-0.432***	-0.284***	-0.331***	-0.232***
			[0.090]	[0.061]	[0.073]	[0.060]
Economy Traits*COVID-19	No	Yes	Yes	No	Yes	No
Firm Traits*COVID-19	No	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Economy-Week FE	No	No	No	Yes	No	Yes
No. Observations	45422	45422	45422	45409	122504	122469
No. Firms	3545	3545	3545	3544	3546	3545
Adjusted R-Squared	0.457	0.458	0.459	0.518	0.379	0.445

Notes: In all the regression displayed in this table, the dependent variable is the *Weekly Stock Returns*. Economy traits include GDP *per capita*, the growth rate of GDP, % population above 65 years-old and a set of dummy variables for the countries' legal origin. Firm traits are composed by: *Firm size*, *Leverage*, *Cash*, *Return on Assets*. Both economy and firm traits refer to the year of 2018. Columns 1-4 refer to the first quarter of 2020, while columns 5 and 6 report the results for the extended time-period (until 28$^{\text{th}}$ August). Robust standard errors clustered at the economy level are reported in brackets. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Response of firms' financial and performance indicators to COVID-19

	(1)	(2)	(3)	(4)
	Log (Net Sales)	Return on Assets	Debt/Assets	CAPEX/Assets
2020 Q1	-0.011***	-0.758***	0.509	-0.271***
	[0.003]	[0.274]	[0.385]	[0.086]
2020 Q2	-0.016***	-0.958***	1.087***	-0.366***
	[0.002]	[0.217]	[0.244]	[0.100]
Log (Total Assets)	0.502***	4.685	15.397***	-0.302
	[0.134]	[4.555]	[5.469]	[0.521]
Cash/Assets	0.009	-19.516	20.435***	-2.208
	[0.164]	[13.026]	[3.345]	[2.998]
Market-to-Book Ratio	-0.001	0.023	0.041	-0.037*
	[0.001]	[0.064]	[0.058]	[0.019]
Debt/Assets	-0.003**	-0.173**		0.009
	[0.001]	[0.071]		[0.012]
Return on Assets	0.003***		-0.225***	0.026***
	[0.001]		[0.054]	[0.007]
Working capital/Assets	0.362*	11.958	-37.250***	-1.759**
	[0.200]	[9.753]	[10.627]	[0.776]
Firm FE	Yes	Yes	Yes	Yes
No. Observations	3018	3008	3010	2984
No. Firms	544	539	540	535
Adjusted R-Squared	0.996	0.835	0.920	0.906

Notes: This table reports the behavior of several financial and performance indicators during the first half of 2020 (pandemic period). Robust standard errors clustered at the economy level are reported in brackets. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Firms' immunity to supply-chain disruptions

	First quarter 2020				January-August 2020	
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19	-3.220**		-3.204**		-3.203*	
	[1.531]		[1.533]		[1.740]	
Suppliers' Exposure	-0.264*	-0.167*	-0.263*	-0.161*	-0.187*	-0.155*
	[0.151]	[0.095]	[0.151]	[0.092]	[0.107]	[0.082]
Suppliers' Exposure * Dummy	0.173	0.295**			0.175**	0.319**
Japanese Suppliers 2011	[0.121]	[0.143]			[0.086]	[0.136]
Suppliers' Exposure * Number of			0.111**	0.131**		
Japanese Suppliers 2011			[0.047]	[0.061]		
Economy Traits*COVID-19	Yes	No	Yes	No	Yes	No
Firm Traits*COVID-19	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Economy-Week FE	No	Yes	No	Yes	No	Yes
No. Observations	25292	25242	25292	25242	68216	68070
No. Firms	1972	1969	1972	1969	1972	1969
Adjusted R-Squared	0.506	0.564	0.506	0.565	0.436	0.501

Notes: In all the regression displayed in this table, the dependent variable is the *Weekly Stock Returns*. Economy traits include GDP *per capita*, the growth rate of GDP, % population above 65 years-old and a set of dummy variables for the countries' legal origin. Firm traits are composed by: *Firm size*, *Leverage*, *Cash*, *Return on Assets*. Both economy and firm traits refer to the year of 2018. Columns 1-4 refer to the first quarter of 2020, while columns 5 and 6 report the results for the extended time-period (until 28th August). Robust standard errors clustered at the economy level are reported in brackets. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

8 Appendix

Figure A1. Weekly average stock market returns - first quarter of 2020

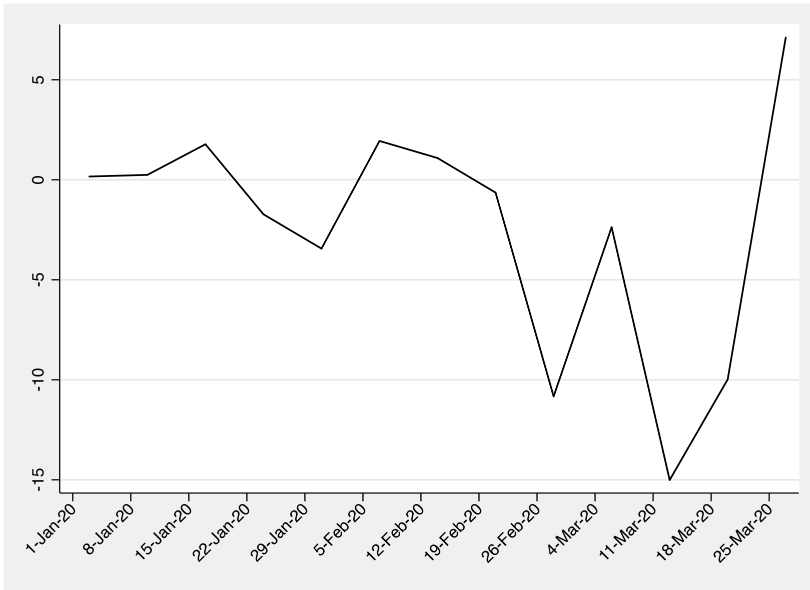
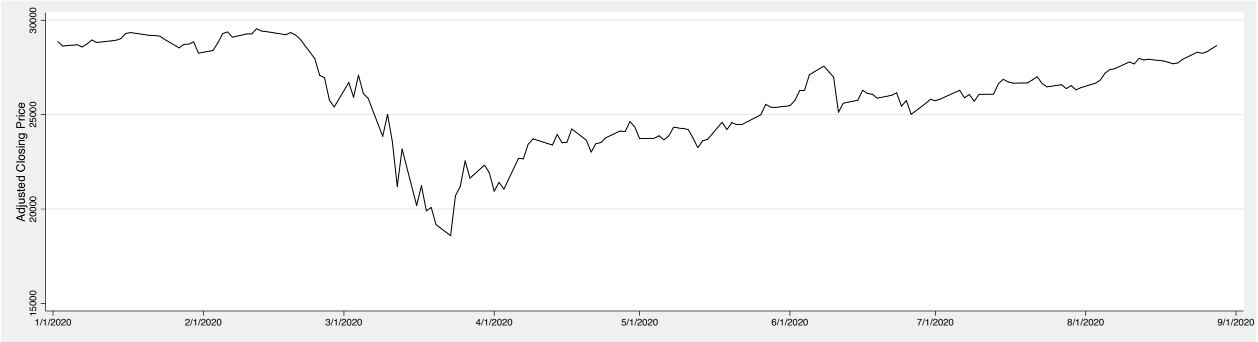
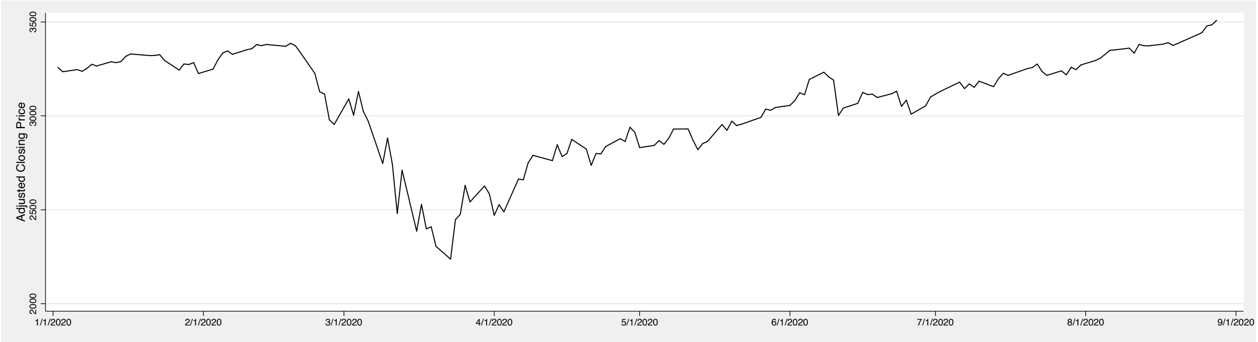


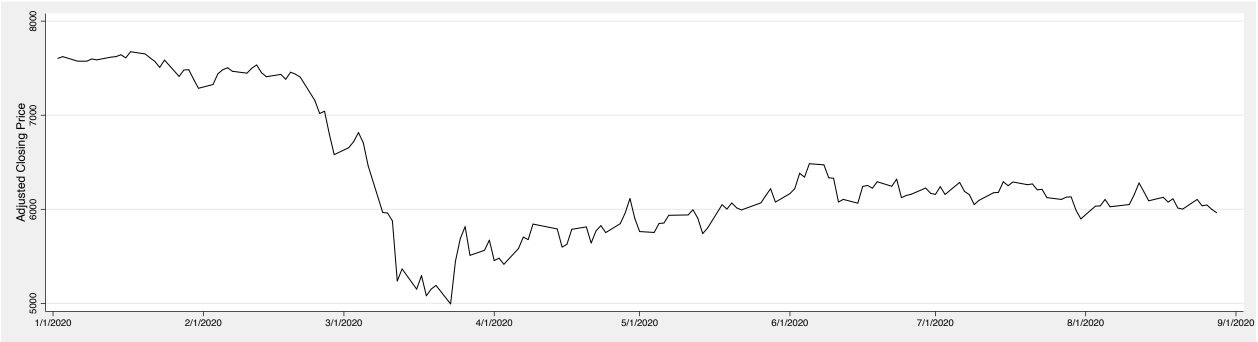
Figure A2. Evolution of the stock indexes in 2020



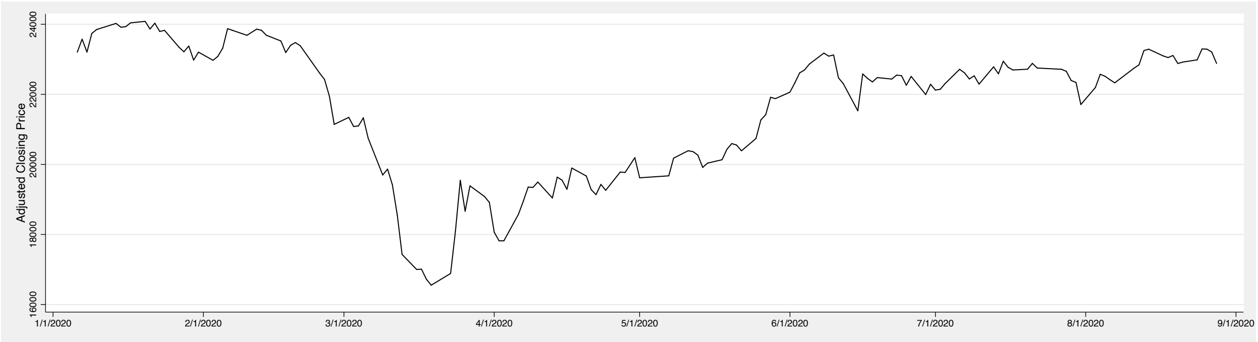
(a) Dow Jones Index



(b) S&P 500



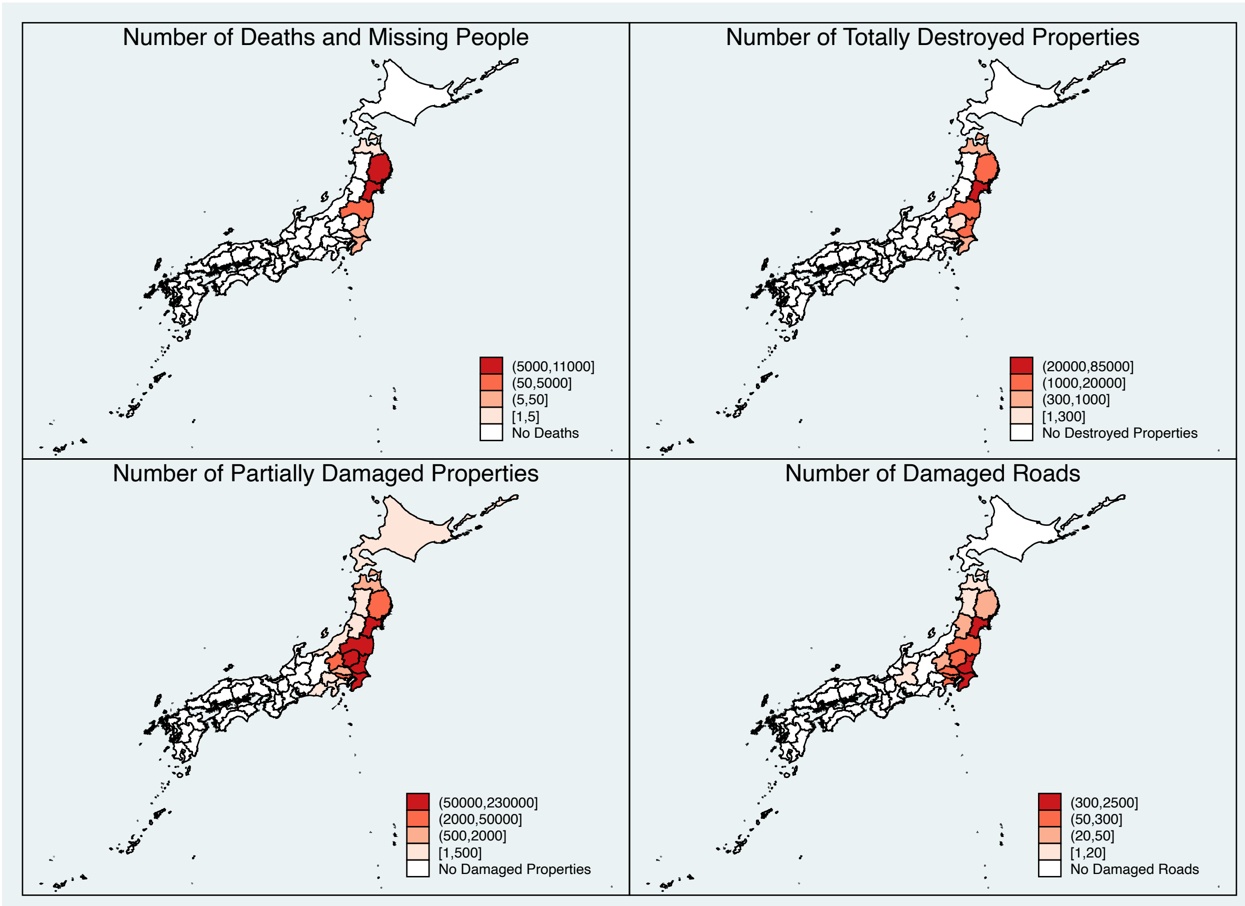
(c) FTSE 100



(d) Nikkei 225

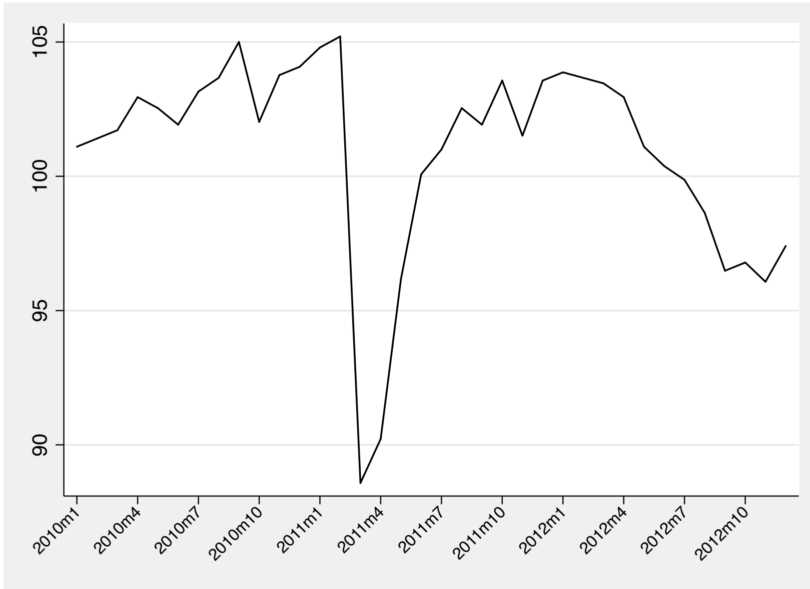
Source: Yahoo Finance

Figure A3. Damages caused by The Great East Japan Earthquake, by prefecture



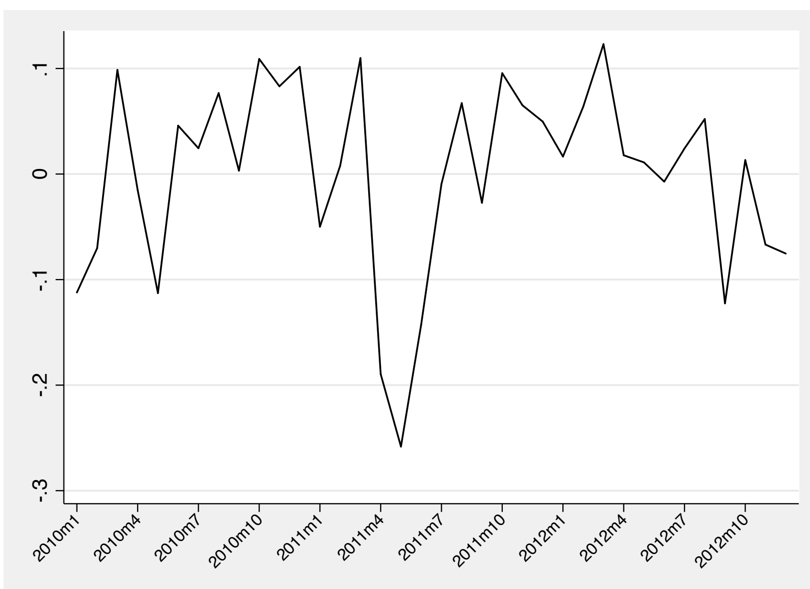
Source: National Police Agency Japan

Figure A4. Index of Japanese Industrial Production (base year=2015)



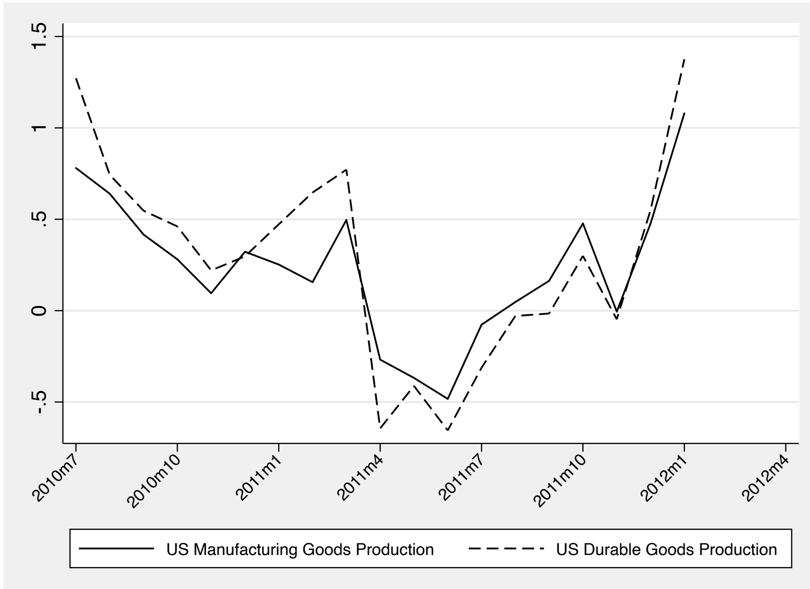
Source: OECD (2020), Industrial production (indicator).
Notes: Industrial production refers to the output of industrial establishments and covers sectors such as mining, manufacturing, electricity, gas and steam and air-conditioning.

Figure A5. US Imports from Japan (logarithm form)



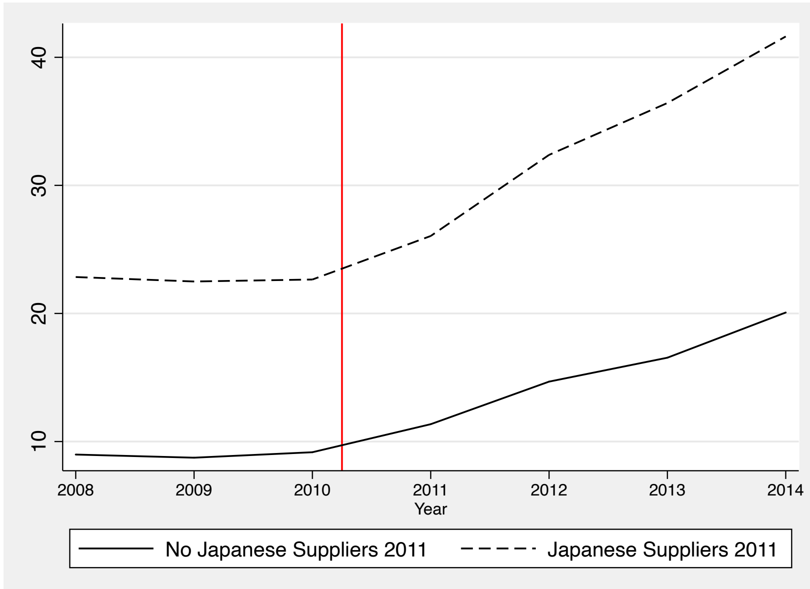
Source: US Census Bureau.
Notes: The series is logged and HP-filtered.

Figure A6. US Industrial Production: Manufacturing and Durable Goods

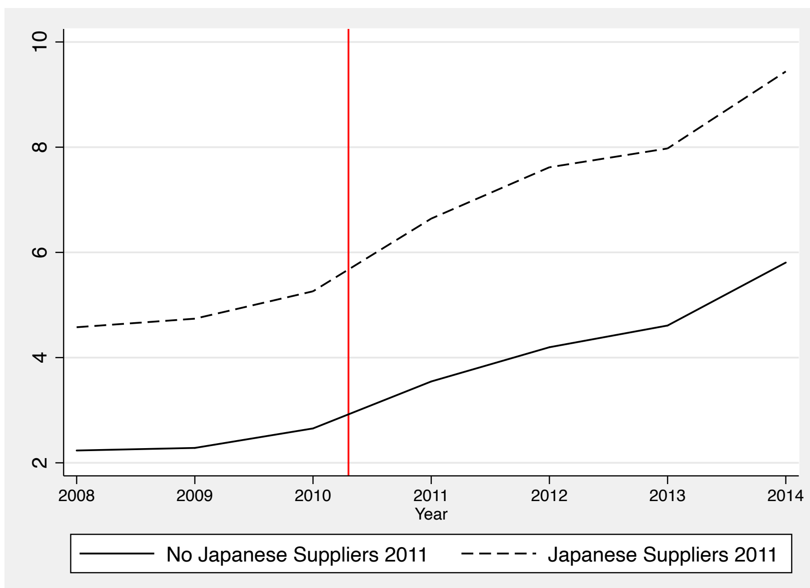


Source: Federal Reserve Board.
Notes: The series is seasonally adjusted and HP-filtered.

Figure A7. Simple average of the outcomes for both groups of firms 2008-2014



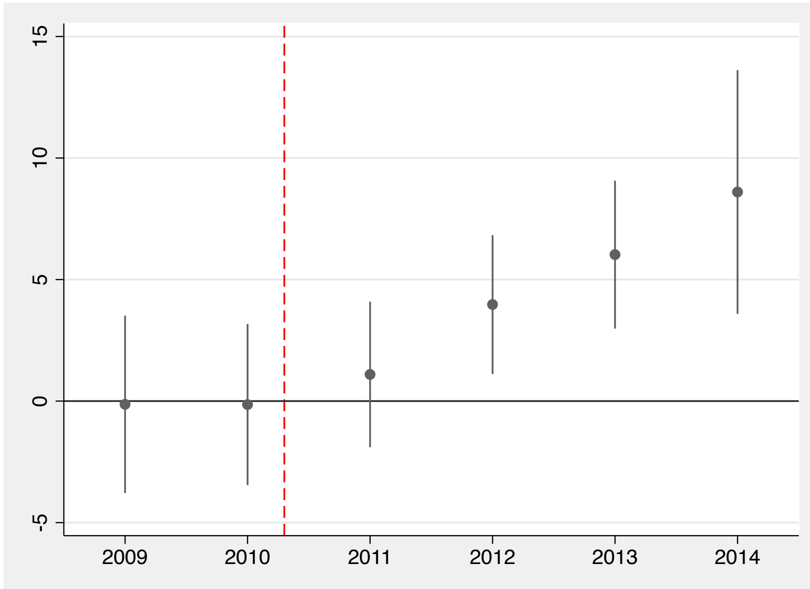
(a) *Total Number of Suppliers*



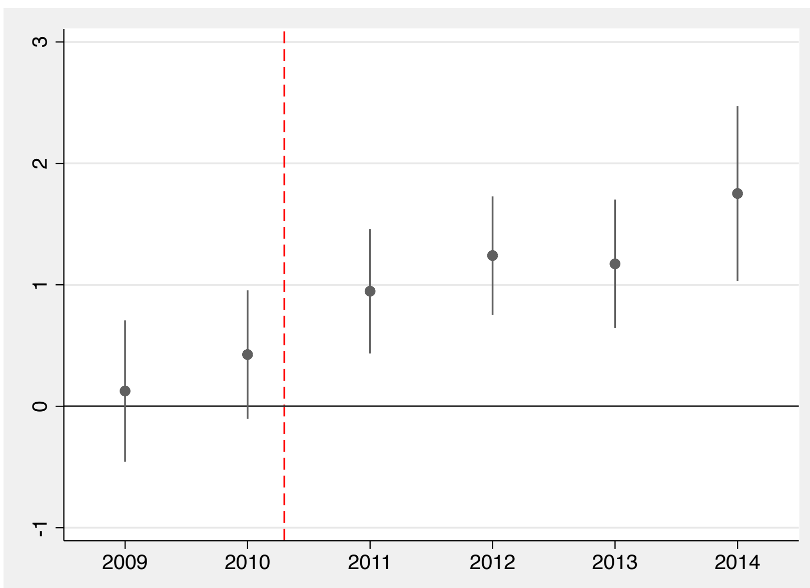
(b) *Number of Supplier Countries*

The red line indicates The Great East Japan Earthquake.

Figure A8. Production network's diversification 2008-2014



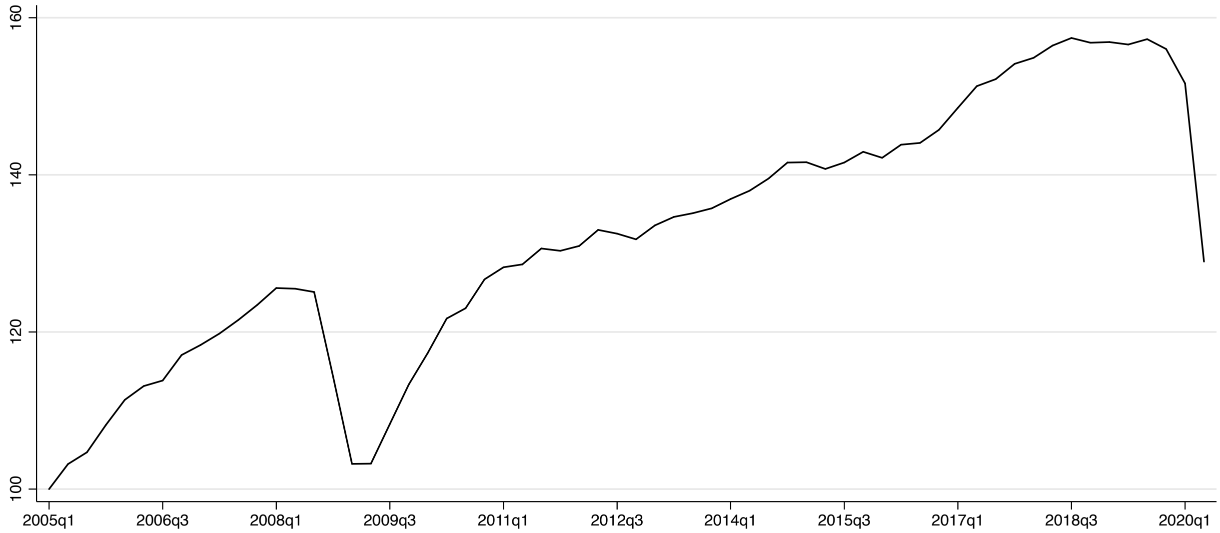
(a) Outcome variable: *Total Number of Suppliers*



(b) Outcome variable: *Number of Supplier Countries*

Figures A8a and A8b are built based on the results of the model reported in equation (5), which can be found in columns 1 and 2 of table 2. They depict graphically the estimated coefficients and the 95% confidence intervals on the interaction terms between the year-dummies and the variable *Dummy Japan Suppliers 2011* (the treatment variable), for each year between 2009 and 2014. The red dashed line indicates The Great East Japan Earthquake.

Figure A9. Volume Index of Merchandise Exports and Imports, World (base year=2005)



Source: United Nations Conference on Trade and Development (UNCTAD).
Notes: The series is seasonally adjusted.

Table A1. Number of firms in the sample, by country

Country	No. of Firms	Country	No. of Firms
Argentina	23	Kuwait	5
Australia	199	Luxembourg	15
Austria	25	Malaysia	49
Bahrain	4	Mexico	33
Belgium	32	Morocco	1
Brazil	47	Netherlands	50
Canada	3	New Zealand	39
Chile	30	Norway	38
China	48	Oman	4
Colombia	8	Pakistan	2
Cyprus	2	Peru	15
Czech Republic	2	Philippines	21
Denmark	32	Poland	26
Egypt, Arab Rep.	6	Portugal	11
Finland	29	Russian Federation	32
France	122	Saudi Arabia	17
Germany	127	Singapore	40
Greece	14	South Africa	78
Hong Kong SAR, China	96	Spain	49
Hungary	3	Sweden	100
India	93	Switzerland	83
Indonesia	37	Thailand	32
Ireland	31	Turkey	38
Israel	15	United Arab Emirates	10
Italy	56	United Kingdom	35
Korea, Rep.	115	United States	1529
Total			3551

Table A2. Variables' description

Variable	Description
Panel A: Diversification 2008-2014	
Share of Diff. Inputs	Share of each firm's suppliers producing differentiated goods
Panel B: replication procedure	
Weekly Stock Return	Percentage variation in firm's dividend-ajusted closing price computed using the last trading day of the week
COVID-19	Weekly growth rate of cumulative COVID-19 confirmed infections in a given economy
Suppliers' Exposure	Weighted average of COVID-19 among the supplier countries, where the weights are given by the pre-pandemic number of suppliers from each country and COVID-19 varies weekly
Firm Size	Natural logarithm of the book value of total assets, in 2018
Leverage	Percentage of total debt over total assets, in 2018
Cash	Cash and equivalents divided by total assets, in 2018
Return on Assets	Ratio of net income over total assets, in 2018
Log (GDP per capita)	Natural logarithm of the GDP per capita, in 2018
GDP growth	The growth rate of GDP, in 2018
% pop. above 65	Percentage of population above 65 years-old, in 2018
Legal Origin	Dummy variables for the legal origin of the country: English, French, German or Scandinavian origin
Panel C: corporate fundamentals	
Log(Net Sales)	Natural logarithm of firm's net sales (or revenues), which correspond to the gross sales minus allowances, returns and discounts
Return on Assets	The ratio of firm's net income to total assets
Debt/Assets	The ratio between firms' total debt and total assets
Log(Total Assets)	Natural logarithm of the firm's book value of total assets
Cash/Assets	Firm's cash and short-term investments over total assets
Working Capital/Assets	The difference between firm's current assets and current liabilities, over total assets
Market-to-Book Ratio	The ratio between firm's market capitalization and its total book value